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Remaining-Useful-Life prognostics for opportunistic grouping of maintenance of landing gear brakes for a fleet of aircraft

Juseong Lee [1], Ingeborg de Pater [2], Stan Boekweit [3] and Mihaela Mitici [4]

[1,2,3,4] *Delft University of Technology, Faculty of Aerospace Engineering, Delft, 2629HS, the Netherlands*
J.Lee-2@tudelft.nl
I.I.dePater@tudelft.nl
stanboekeit@gmail.com
M.A.Mitici@tudelft.nl

ABSTRACT

Several studies have proposed Remaining-Useful-Life (RUL) prognostics for aircraft components in the last years. However, few studies focus on integrating these RUL prognostics into maintenance planning frameworks. This paper proposes an optimization model for opportunistic maintenance scheduling of aircraft components that integrates RUL prognostics and that groups the maintenance of these components to reduce costs. We illustrate our approach for the maintenance of a fleet of aircraft, each equipped with multiple landing gear brakes. RUL prognostics for the landing gear brakes are obtained using a Bayesian regression model. Based on these RUL prognostics, we group the replacement of brakes using an integer linear program. As a result, we obtain a cost-optimal RUL-driven opportunistic-maintenance schedule for the brakes of a fleet of aircraft. Compared with traditional maintenance strategies, our approach leads to a reduction of up to 20% of the total maintenance costs.

1. INTRODUCTION

Remaining-useful-life (RUL) prognostics are regarded as a key enabler for predictive aircraft maintenance (Sprong, Jiang, & Polinder, 2019). Using RUL prognostics, predictive maintenance aims to perform maintenance tasks in anticipation of failures of aircraft components. The expected impact of predictive maintenance is to reduce unexpected failures, increase system availability, and reduce overall maintenance costs (Lee & Mitici, 2022).

Several studies have proposed algorithms for RUL prognostics for various aircraft systems. For example, Mitici and de Pater develop prognostics for aircraft cooling units using particle filtering. Lee and Mitici propose a regression model to characterize the degradation of aircraft landing gear brakes. Eleftheroglou et al. present the data-driven prognostics for batteries of unmanned aerial vehicles. de Pater, Reijns, and Mitici predict the RUL of aircraft engines using a convolutional neural network and the C-MAPSS data set (Saxena & Goebel, 2008).

Despite the increasing number of RUL prognostics for aircraft systems, few studies integrate these prognostics into actual maintenance planning frameworks to prescribe RUL-driven maintenance tasks (de Jonge & Scarf, 2020; de Pater & Mitici, 2021; Kim, Choi, & Kim, 2022). Such integration is particularly complex since aircraft maintenance planning should consider, apart from RUL prognostics, additional factors such as the flight schedule, the limited availability of the hangar where aircraft are maintained, the cost of different maintenance tasks, and the management of spare parts (de Pater & Mitici, 2021).

Moreover, when considering multiple components, it is desirable to group maintenance tasks to reduce maintenance setup costs (Wildeman, Dekker, & Smit, 1997; Bouvard, Artus, Bérenguer, & Cocquempot, 2011). The approach of grouping maintenance tasks is referred to as opportunistic maintenance (OM). Several studies have proposed OM for various applications, especially for the maintenance of wind turbines (Vu, Do, Fouladirad, & Grall, 2020; Aizpurua, Catterson, Papadopoulos, Chiacchio, & D'Urso, 2017; Xia et al., 2021). However, existing studies are not readily applicable for predictive maintenance of a fleet of aircraft because they consider neither RUL prognostics (Vu et al., 2020), nor the limited availability of critical resources such as hangars (Aizpurua et al., 2017), nor the fact that the flight schedule of aircraft restricts the planning of maintenance (Xia et al., 2021). Thus, these critical constraints need to be considered for the OM for a fleet of aircraft.

In this paper, we integrate RUL prognostics of aircraft components into opportunistic maintenance (OM) for a fleet of aircraft. Our approach groups maintenance tasks for aircraft components based on their RUL prognostics. The goal of grouping the maintenance of the components is to reduce maintenance setup costs, i.e., the costs needed to initiate maintenance. We illustrate our approach for landing gear brakes of a fleet of aircraft. We first propose a Bayesian linear regression model to predict the RUL of aircraft landing gear brakes. The obtained RUL prognostics are validated against sensor measurements obtained during the actual operation of the aircraft. Then, taking into account these RUL prognostics, we propose an integer linear programming model to opportunistically plan maintenance for the brakes. Our model considers the limited availability of hangars where maintenance can be performed, as well as realistic flight schedules. The result shows that the proposed RUL-driven OM reduces by 20% the expected total maintenance cost for the brakes of a fleet of aircraft compared to traditional maintenance approaches.

2. RUL Prognostics for Aircraft Landing Gear Brakes

2.1. Maintenance of aircraft landing gear brakes

We consider the maintenance of landing gear brakes of wide-body aircraft. A wide-body aircraft is equipped with 8 landing gear brakes, 4 on each side of the wings. The carbon disks of the brakes are worn out when the aircraft decelerates. As soon as the remaining thickness of a braking disk is below an operational threshold, it needs to be replaced before the aircraft can perform another flight.

According to current maintenance practice, aircraft landing gear brakes are inspected periodically (Lee & Mitici, 2020). Every d flight cycles, mechanics measure the remaining thickness of the brakes. If the remaining thickness is below a predefined threshold, then the brake is replaced with a new one. In order to ensure a high reliability, the inspection interval d is often short, i.e., frequent inspections. Using RUL prognostics, predictive maintenance aims to reduce the wasted life of brakes due to too-early replacements, while limiting the cases when the degradation of a brake may unexpectedly exceed an operational threshold.

2.2. Condition monitoring of aircraft landing gear brakes

New aircraft are equipped with brake condition monitoring systems that measure the thickness of the brake disks. The thickness of a disk is a direct measure of the degradation level of a brake. Formally, let us denote the degradation level of a brake after ϕ^{th} flight cycle as Z_ϕ. We normalize this degradation level so that $Z_\phi = 0$ when the brake is new. As soon as $Z_\phi > \eta$, where $\eta = 1$ following normalization, the brake needs to be replaced. As soon as $Z_\phi > \eta$, we say that the brake becomes *inoperable*.

In this study, we analyze the actual brake degradation data

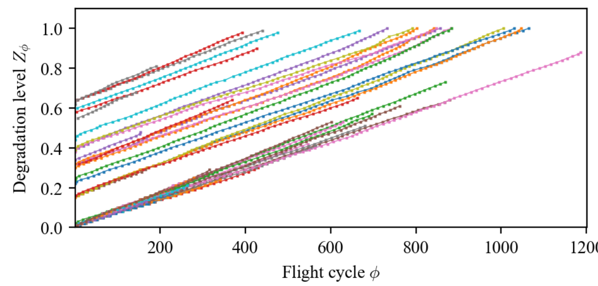

Figure 1. The degradation data of landing gear brakes.

collected from a fleet of aircraft. These aircraft have been in operation for a period of 6 months up to 3 years. Figure 1 shows the normalized degradation data recorded for several aircraft. The x-axis is the number of flight cycles (ϕ) during which a brake was used, and the y-axis is the degradation level (Z_ϕ) of the brakes. The line segments of different colors represent different brakes. Figure 1 shows that the degradation of a brake continuously and stochastically increases over time.

Under predictive maintenance, the goal is to use the information provided by RUL prognostics to replace brakes just before their degradation reaches an operational threshold ($\eta = 1$). In Figure 1, the end of a line segment is the moment when the brake is replaced under the current practice. We note that in current practice, RUL prognostics are not yet utilized to plan maintenance. Often, brakes are preventively replaced before their degradation level reaches threshold η, wasting the useful life of the brakes. Using RUL prognostics, the aim is to achieve a higher utilization of the brakes while minimizing maintenance costs.

2.3. RUL prognostics of aircraft landing gear brakes

Given the brake degradation data recorded for a fleet of aircraft, we use a Bayesian linear regression (BLR) to predict the remaining-useful-life (RUL) of the brakes. For the brake degradation data in Figure 1, its linearity allows the BLR model to achieve accurate RUL predictions compared to advanced non-linear models such as artificial neural networks (Oikonomou, Eleftheroglou, Freeman, Loutas, & Zarouchas, 2022). The input of the BLR model is the number of flight cycles ϕ, and the output is the (predicted) degradation level of a brake after this flight cycle $\hat{Z}_\phi$. Formally, we consider the following probabilistic model:

$$P\left(\hat{Z}_\phi \middle| \phi, \omega, \sigma\right) = \mathcal{N}\left(\hat{Z}_\phi \middle| \phi\omega, \sigma^2\right), \tag{1}$$

where ω is the coefficient of the linear model, and σ^2 is the variance of the Gaussian model. The prior of the coefficient ω is assumed to be zero-mean Gaussian, i.e., $P(\omega) = \mathcal{N}(\omega|0, \lambda\mathbf{I})$. Here, λ and σ^2 are the hyper-parameters of the model, and we consider a Gamma distribution as their prior. Finally, the parameters ω, λ, and σ^2 are jointly optimized by maximizing the log marginal likelihood (Pedregosa et al., 2011).

Then, given that a brake is already operated for ϕ flight cycles, its RUL $\rho(\phi)$ is the number of remaining flight cycles until the probability that the degradation level exceeds η is larger than a threshold ξ, i.e.,

$$\rho(\phi) = \min_{\delta} \left\{ \delta : P\big(\hat{Z}_{\phi+\delta} \geq \eta \big| Z_{\phi}\big) \geq \xi \right\}, \qquad (2)$$

where ξ is a given reliability threshold.

The RUL prognostics of the brakes are updated after every flight cycle, taking into account the most recently available degradation data collected from the on-board condition monitoring systems.

A result of RUL prognostics of a brake in the actual data set is shown in Figure 2. We predict the RUL of this brake after it has been operated for 748 flight cycles. Given the degradation, the degradation level is expected to exceed $\eta = 1$ after 40 flight cycles with probability $\xi = 0.5$, and thus, the predicted RUL is $\rho(\phi) = 40$. Given the true RUL $\rho^* = 44$, the error of the RUL prediction is -4 flight cycles.

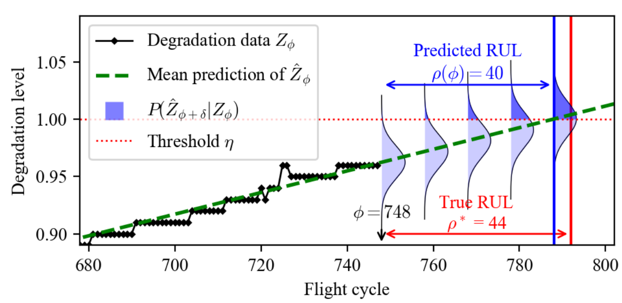

Figure 2. Result of RUL prognostics obtained for a brake in the data set. The predicted RUL is 40 cycles and true RUL is 44 cycles.

2.4. Performance of the RUL prognostics

The performance of the proposed RUL prognostics using BLR is validated based on the actual degradation data collected from a fleet of aircraft. We consider the sensor measurements of 40 brakes of a fleet of aircraft which have been operated in real-life conditions. Each of these 40 brakes have been operated for ϕ^* flight cycles until these brakes become inoperable, i.e., $Z_{\phi^*} = \eta$. Their recorded degradation data are used as a test set for our BLR model since we know the true RUL of the 40 brakes.

We apply BLR at several moments during the operation of the brakes: at 200, 100, 50, and 25 flight cycles before the brakes become inoperable, i.e., the true RUL at these moments in time is $\rho^* \in \{200, 100, 50, 25\}$ flight cycles. We predict the RUL of 40 test brakes at these moments, and plot the box plots of the error $\rho - \rho^*$ in Figure 3. We also determine the mean-bias-error (MBE) and root-mean-squared-error (RMSE) as follows:

$$\text{MBE} = \frac{1}{K} \sum_{k=1}^{K} (\rho_k - \rho_k^*),$$

$$\text{RMSE} = \frac{1}{K} \sqrt{\sum_{k=1}^{K} (\rho_k - \rho_k^*)^2},$$

where $K = 40$ brakes considered. Table 1 shows the MBE and RMSE of the proposed RUL prognostics.

The error of the RUL prognostics is smaller when true RUL is smaller, i.e., the accuracy of the prognostics increases as we approach the time of failure. In particular, MBE is smaller than 2 flight cycles when the true RUL is 100 flight cycles (see Table 1). Considering the fact that an aircraft makes 2 flights per day on average, the bias of the prognostics is roughly 1 day only. Moreover, the RMSE decreases to 5.4 flight cycles, which is very small considering the average useful life of the brakes in our model (approximately 1250-1450 flight cycles) (Lee & Mitici, 2022). Based on this performance of the BLR, we conclude that our prognostics are reliable to be used for maintenance scheduling.

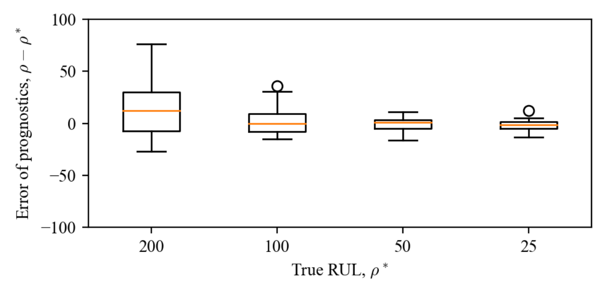

Figure 3. Error of the RUL prognostics for the brakes in the data set.

Table 1. Performance of the proposed RUL prognostics for the brakes in the data set.

True RUL ρ^* [Flight cycles]	**200**	**100**	**50**	**25**
MBE [Flight cycles]	8.4	1.7	-0.5	-1.7
RMSE [Flight cycles]	41.3	12.4	6.0	5.4

3. Integration of RUL Prognostics into Opportunistic Maintenance Scheduling

We propose a RUL-driven opportunistic maintenance planning (RUL-driven OM) for a set of generic aircraft components whose degradation is monitored over time and whose RUL is updated over time. We propose an integer linear programming (ILP) model to group maintenance tasks for these components considering their RUL prognostics.

3.1. Problem description

Our goal is to schedule the maintenance of multiple components of a fleet of aircraft, while minimizing the total maintenance cost. We consider M aircraft ($i \in \mathcal{I} = \{1, \dots, M\}$), each equipped with N components ($j \in \mathcal{J} = \{1, \dots, N\}$). The aircraft perform a sequence of flights according to a flight schedule. Figure 4 shows an example of a historical flight schedule. The components are used during flight-time when their degradation evolves stochastically over time. Based on the flight schedule, we define maintenance slots, which are time periods when the aircraft is on-ground at an airport with a hangar. The aircraft can undergo maintenance only at the hangar. Due to the limited space and resources at the hangar, at most H aircraft can be maintained at the same time in the hangar.

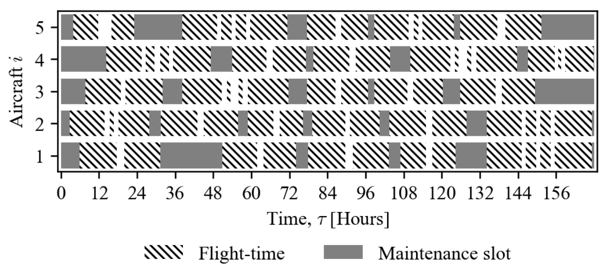

Figure 4. An example of flight schedules for 5 aircraft for a week.

The cost of aircraft maintenance consists of i) the setup cost and ii) the component replacement cost. The setup cost C_{set} is the cost to prepare the maintenance of an aircraft in the hangar. This cost can be reduced if multiple maintenance tasks are grouped and performed together during one hangar visit.

Over time, components are scheduled for replacement several weeks in advance. The cost of a scheduled replacement for a component is C_{sch}. If, however, this component becomes inoperable unexpectedly before the moment of the scheduled replacement, we perform an unscheduled replacement for this component at cost C_{uns}. In general, we assume $C_{\text{uns}} > C_{\text{sch}}$ (Pereira, Gomes, Melicio, & Mendes, 2021).

3.2. Rolling horizon for RUL-driven OM

We consider a sequence of time windows that move forward, using a rolling horizon approach (see Figure 5). The r^{th} time window is the time period $[T_0^r, T_1^r]$. At the beginning of each time window, we update the RUL prognostics using the most recent degradation data collected until $\tau < T_0^r$. In addition, we know the maintenance slots available for the fleet of aircraft during this time window, and the availability of the hangar H. Taking into account this information, we optimize the maintenance schedule for the time window $[T_0^r, T_1^r]$ (see Section 3.3).

Having obtained a maintenance schedule for time window $[T_0^r, T_1^r]$, we roll forward Δ days. The maintenance schedule for the time period $[T_0^r, T_0^{r+1}]$ is fixed, $T_0^{r+1} = T_0^r + \Delta$. If during $[T_0^r, T_0^{r+1}]$ a component becomes inoperable before its scheduled maintenance, then we perform unscheduled maintenance. We next optimize the maintenance schedule for the new time window $[T_0^{r+1}, T_1^{r+1}]$, updating the RUL prognostics.

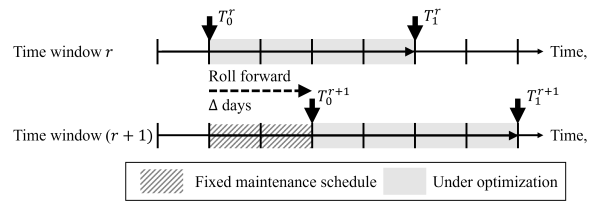

Figure 5. Rolling horizon approach.

3.3. Integer Linear Programming of RUL-driven OM

3.3.1. Decision variables

We define the following two decision variables $x_{i,j,t}$ and $y_{i,t}$:

$$x_{i,j,t} = \begin{cases} 1 & \text{if component } j \text{ of aircraft } i \text{ is scheduled} \\ & \quad \text{for maintenance at time slot } t \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

$$y_{i,t} = \begin{cases} 1 & \text{if aircraft } i \text{ is scheduled for maintenance} \\ & \quad \text{at time slot } t \text{ but not at time slot } (t-1) \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Here, $x_{i,j,t}$ is a binary variable indicating the maintenance schedule, and $y_{i,t}$ is a binary variable indicating the hangar visit of an aircraft. If an aircraft is scheduled for the maintenance of more than 2 components in consecutive time slots, we regard this as one hangar visit, which requires the setup cost once. Thus, $\sum_{t \in \mathcal{T}_i} y_{i,t}$ is the number of hangar visits of aircraft i.

3.3.2. Objective function

We consider the following objective function:

$$\min \sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}_i} \Big(C_{\text{set}} y_{i,t} + \sum_{j \in \mathcal{J}_i} C_{\text{sch}} x_{i,j,t} + \sum_{j \in \mathcal{J}_i} c_{i,j,t} x_{i,j,t} \Big), \tag{5}$$

where the first term is the setup cost for hangar visits, and the second term is the cost for scheduled replacements.

The third term of the objective in Eq. (5) penalizes component replacements that are scheduled too early or too late relative to its predicted RUL. Specifically, the penalty $c_{i,j,t}$ is defined as follows:

$$c_{i,j,t} = \begin{cases} c_1 t - c_2 \rho_{i,j,t} & 0 \geq \rho_{i,j,t} \\ c_3 t & 0 < \rho_{i,j,t} \end{cases}. \quad (6)$$

Here, $\rho_{i,j,t}$ is the estimated RUL of component j of aircraft i at time slot t. This RUL is estimated using the prognostics model introduced in Section 2. Also, we assume that $0 < c_1 < c_2 < c_3$.

An example of a penalty $c_{i,j,t}$ in Eq. (6) is shown in Figure 6. If time slot t is before the moment when component j is expected to become inoperable, i.e., if $\rho_{i,j,t} \geq 0$, then the penalty decreases after each flight cycle. Thus, this penalty incentivizes solutions that schedule replacements when RUL is small, i.e., small wasted useful life. When two time slots t_1 and t_2 have the same RUL ($\rho_{i,j,t_1} = \rho_{i,j,t_2}$), the first term in Eq. (6), $c_1 t$, leads to lower penalties for a replacement scheduled at an earlier time slot. On the other hand, if time slot t is after the moment when component j is expected to become inoperable, i.e., if $\rho_{i,j,t} < 0$, then the penalty rapidly increases by $c_3 t$. Thus, with this RUL related penalty $c_{i,j,t}$, our model avoids scheduling a component replacement at a later time then its predicted RUL.

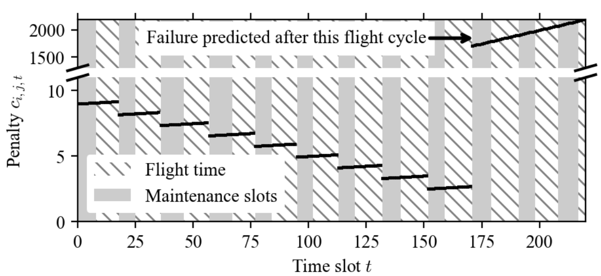

Figure 6. An example of penalty parameter $c_{i,j,t}$ in Eq. (6).

3.3.3. Constraints

The following constraints are considered:

$$\sum_{t \in \mathcal{T}_i} x_{i,j,t} = 1 \quad \forall i \in \mathcal{I}, \forall j \in \mathcal{J}_i, \quad (7)$$

$$\sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}_i} x_{i,j,t} \leq H \quad \forall t \in \mathcal{T}_i, \quad (8)$$

$$\sum_{j \in \mathcal{J}_i} x_{i,j,t} \leq 1 \quad \forall i \in \mathcal{I}, \forall t \in \mathcal{T}_i \quad (9)$$

$$\sum_{j \in \mathcal{J}_i} x_{i,j,t} = 0 \quad \forall i \in \mathcal{I}, \forall t \in \mathcal{T} : t \notin \mathcal{T}_i, \quad (10)$$

$$\sum_{j \in \mathcal{J}_i} x_{i,j,t} - \sum_{j \in \mathcal{J}_i} x_{i,j,(t-1)} \leq y_{i,t} \quad \forall i \in \mathcal{I}. \quad (11)$$

Constraint (7) ensures all components whose RUL is within the time horizon ($j \in \mathcal{J}_i$) are scheduled for replacements exactly once. Constraint (8) ensures that no more than H aircraft are maintained in the hangar at the same time. In addition, constraint (9) ensures that only one component of an aircraft can be maintained during a time slot t. This constraint (9) is necessary only if $H > 1$. If $H = 1$, then constraint (8) is sufficient. Constraint (10) prevents scheduling maintenance outside of available maintenance slots ($t \notin \mathcal{T}_i$).

Lastly, constraint (11) ensures that the variable $y_{i,t}$ satisfies its definition given in Eq. (4). In particular, constraint (11) provides a lower bound of $y_{i,t}$. So, $y_{i,t} \geq 1$ if the aircraft is brought to the hangar at time slot t, i.e., it is scheduled for maintenance at time slot t, but not at time slot $(t-1)$. On the other hand, $y_{i,t} \geq 0$ if the aircraft is at the hangar at both time slots t and $(t-1)$, or if the aircraft is not at the hangar at both time slots t and $(t-1)$. Since we are minimizing the objective and $C_{\text{set}} > 0$ (see the objective in Eq. (5)), the optimal value of $y_{i,t}$ is its lower bound.

4. Numerical Results: Integration of RUL into OM Strategy of Aircraft Landing Gear Brakes

4.1. RUL-driven OM strategy of landing gear brakes

The proposed RUL-driven OM is applied to the maintenance of aircraft landing gear brakes. A wide-body aircraft has 8 brakes ($N = 8$), We consider a fleet of 10 wide-body aircraft ($M = 10$), and assume that at most 1 aircraft can be maintained in a hangar ($H = 1$) at the same time. Using the rolling horizon approach (see Section 3.2), we simulate 10 years of maintenance. The actual degradation of the brakes is shown to follow a Gamma process whose parameters have been estimated in (Lee & Mitici, 2020; van Noortwijk, 2009).

An example of a maintenance schedule generated by our proposed RUL-driven OM is shown in Figure 7. We predict the RUL of components every 2 weeks (the grey vertical lines). The short black vertical lines indicate the moment when the RUL is predicted, the triangles indicate the moment when the component is expected to become inoperable (see Eq. (2)), and the horizontal line segments indicate the length of RUL. Squares indicate the scheduled time of replacements. The optimal solution always allocates the aircraft to maintenance slots within the predicted RUL, i.e., squares are always on the horizontal line segments. The vertical red lines indicate the grouped maintenance tasks. For example, aircraft 1 replaces 6 components with only 3 hangar visits due to grouping: components 5 and 3, components 6 and 2, and components 8 and 4 are grouped together for maintenance. For aircraft 3, component 2 is replaced strictly at RUL without grouping because the closest group of tasks scheduled in November is too early for it, i.e., the benefit of grouping is small.

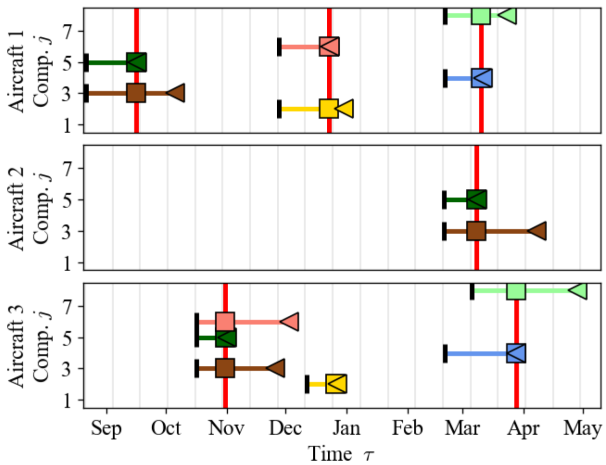

Figure 7. An example of optimal maintenance schedule generated by the proposed RUL-driven OM.

4.2. Benchmarks: traditional maintenance strategies

The performance of the proposed RUL-driven OM is compared with respect to 3 traditional maintenance strategies shown in Table 2. Their schedules are optimized using the ILP in Section 3.3 with modified objective functions, as follows.

1) Preventive maintenance (PM)

Under preventive maintenance (PM), the brakes are replaced at fixed time interval, without making use of the updated condition data or RUL prognostics. Thus, the PM schedule is obtained by modifying the penalty parameter $c_{i,j,t}$ in Eq. (6) as follows:

$$c_{i,j,t} = \begin{cases} c_1 t - c_2(d_{i,j} - \phi_{i,t}) & \phi_{i,t} \leq d_{i,j} \\ c_3 t & \phi_{i,t} > d_{i,j} \end{cases}. \tag{12}$$

Here, $d_{i,j}$ is the deadline to replace brake j of aircraft i, and it is assumed to be the mean-cycles-to-failure of the brakes estimated in (Lee & Mitici, 2020). Also, we set $C_{\text{set}} = 0$ in the objective function in Eq. (5) since the setup cost is not considered under PM.

2) Opportunistic maintenance (OM)

Opportunistic maintenance (OM) also replaces components at fixed time intervals, but it does consider the grouping of maintenance tasks to minimize the setup cost. Thus, for OM, we consider a nonzero C_{set} in the objective function in Eq. (5), and the penalty parameter $c_{i,j,t}$ defined in Eq. (12).

Table 2. Comparison of benchmark strategies.

Strategy	Replacement based on	Considering hangar setup cost
PM	Fixed-interval	No
OM	Fixed-interval	Yes
RUL-driven M	RUL-prognostics	No
RUL-driven OM	RUL-prognostics	Yes

3) RUL-driven maintenance (M)

RUL-driven maintenance (M) schedules all component replacements at the predicted RUL, but without grouping these components. The objective function of RUL-driven M has the same penalty parameter $c_{i,j,t}$ defined in Eq. (6). However, grouping is not performed as setup cost at hangar is not considered, i.e., $C_{\text{set}} = 0$.

4.3. RUL-driven OM vs benchmark maintenance strategies

We perform Monte Carlo simulation to evaluate the expected long-run cost of the maintenance strategies in Table 2. The long-run cost is defined as:

$$C = C_{\text{set}} N_{\text{hv}} + C_{\text{sch}} N_{\text{sch}} + C_{\text{uns}} N_{\text{uns}}. \tag{13}$$

Here, N_{hv}, N_{sch}, and N_{uns} are the number of hangar visits, the number of scheduled replacements, unscheduled replacements, per year per aircraft, respectively. These values (N_{hv}, N_{sch}, and N_{uns}) are evaluated by Monte Carlo simulations (10^3 runs). Also, C_{set}, C_{sch}, and C_{uns} are the setup cost of a hangar visit, the cost of a scheduled replacement, and the cost of unscheduled replacement, respectively (see Section 3.1) for unscheduled replacements). The parameters C_{set}, C_{sch} and C_{uns} depend on the cost model of an aircraft operator. For this case study, we assume $C_{\text{set}} = 1$, $C_{\text{sch}} = 1$, and $C_{\text{uns}} = 2$.

The simulation results in Figure 8 and Table 3 show the benefit of utilizing RUL prognostics and considering component grouping, i.e., the benefit of the proposed RUL-driven OM. Figure 8 shows that the RUL-driven OM results in the lowest expected cost per aircraft per year. The results show that RUL-driven OM leads to 20% lower costs than PM, which is the traditional maintenance strategy.

Table 3 shows two reasons why the RUL-driven OM achieves the lowest expected cost. First, it has the smallest number of unscheduled replacements because it optimizes the mo-

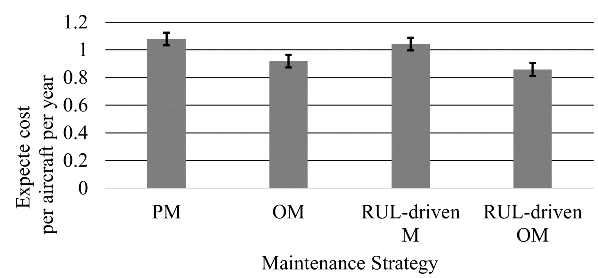

Figure 8. Expected cost and its 95% confidence interval.

Table 3. Performance of benchmarks.

	PM	**OM**	**RUL-driven M**	**RUL-driven OM**
Maintenance cost C	1.078	0.919	1.042	0.858
Scheduled replacements N_{sch}	0.255	0.327	0.291	0.370
Unscheduled replacements N_{uns}	0.223	0.154	0.186	0.111
Hangar visits N_{hv}	0.377	0.285	0.379	0.266

ment of replacements using RUL prognostics. Second, the RUL-driven OM results in the smallest number of hangar visits, saving the setup cost. Compared to the OM that minimizes the setup cost without considering RUL prognostics, the RUL-driven OM further reduces the number of hangar visits.

In Table 3, it is also interesting to see that the total number of scheduled and unscheduled replacements are roughly the same for all strategies, e.g., $N_{\text{sch}} + N_{\text{uns}} \approx 0.47$. This implies that the best maintenance strategy does not reduce the total number of replacements, but rather optimizes the timing of the replacements so that there is sufficient time to prepare tasks in advance, and reduce the setup cost.

5. Conclusion

In this study, we integrate Remaining-Useful-Life (RUL) prognostics for aircraft components into opportunistic maintenance planning that groups the maintenance of multiple components. First, the RULs of aircraft landing gear brakes are estimated based on a Bayesian regression model and the actual degradation data collected from a fleet of aircraft. Then, these prognostics are integrated into a maintenance planning optimization - opportunistic maintenance. With this, we group replacements of several brakes to reduce the setup cost for hangar visits. The proposed maintenance planning is applied for a long time horizon using a rolling horizon. Finally, the numerical results show that our proposed RUL-driven opportunistic maintenance planning results in a 20% reduction of total costs compared with several traditional maintenance strategies.

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BIOGRAPHIES

Juseong Lee is a PhD candidate at the Air Transport and Operations Section, Faculty of Aerospace Engineering, Delft University of Technology. He holds an MSc degree in Aerospace Engineering from Korea Advanced Institute of Science and Technology (KAIST). His research interest includes the design and optimization of complex systems such as aircraft predictive maintenance.

Ingeborg de Pater is a PhD candidate at the Faculty of Aerospace Engineering, Delft University of Technology, the Netherlands. Her research interests are predictive aircraft maintenance scheduling and the Remaining Useful Life estimation of aircraft components.

Stan Boekweit has a MSc degree from Aerospace Engineering from the Air Transport and Operations Section, Faculty of Aerospace Engineering, Delft University of Technology.

Mihaela Mitici is an Assistant Professor at the Air Transport and Operations Section, Faculty of Aerospace Engineering, Delft University of Technology. She has a PhD in Stochastic Operations Research from University of Twente, the Netherlands. She specializes in Operations Research, with a focus on stochastic processes, decision-making under uncertainty, applied probability theory. Her main application domains are predictive aircraft maintenance, airport operations, and urban air mobility.